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Modeling of financial early warnings in integrating the monitoring processes of financial resources and solvency of insurance companies

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Abstract

Several studies have evaluated financial solvency using the stress test and its consequences in insurance companies. This study modelled financial solvency in insurance companies using Bayesian averaging and Wilson's model. This applied and correlational study was conducted on 27 insurance companies admitted to the Tehran Stock Exchange from 2002 to 2006 and 2015 to 2020 to estimate the model. Among the BMA, TVP-DMA, TVP-DMS, BVAR, and OLS models, the BMA model was evaluated as having the highest efficiency in identifying the essential variables affecting financial prosperity. Thus, 40 variables (in 2 categories of early warning indicators and monitoring indicators) affecting financial solvency were included in the Bayesian averaging model, and 13 variables were identified as non-fragile variables based on previous probabilities. These variables included economic growth, inflation uncertainty, exchange rate, sanctions liquidity ratio, capital return ratio, debt ratio, total debt-to-equity ratio, long-term debt-to-equity ratio, surplus contribution (through reinsurance) to surplus, return on investment, and adjusted liabilities to current assets. Out of 13 variables, three variables were in the category of monitoring indicators, and 10 indicators were in the field of early warning variables. Based on the results, the contribution of early warning variables in predicting the crisis of financial prosperity is more important.

Keywords: early warning systems, insurance, financial solvency, Bayesian averaging models, time variable parameter

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1 Introduction

A stable and healthy insurance industry is essential for preserving economic stability against economic shocks by providing an efficient risk transfer mechanism [74]. The stability of the insurance industry is critical for preserving economic stability against financial shocks by providing a suitable mechanism for risk transfer. In addition, the insurance industry provides significant investment funds in an economy by taking advantage of the obligation nature

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rather than the demand nature. Dean et al. [26] found that insurance companies create a sense of security for people, businesses, and governments, promote peace of mind, and reduce anxiety and depression. Buying an insurance policy helps people protect their durable goods from most threats. A thriving insurance industry can provide property security and jobs by covering financial risks [38]. Puławska [65] claims that financial bankruptcy of insurers is a common phenomenon in today's world. According to legislators, financial bankruptcy happens when a company faces financial problems and can no longer fulfill its long-term and short-term obligations. As a result, forecasting the factors affecting the wealth of insurance companies makes it possible to prevent the high costs of bankruptcy of insurance companies [18]. Financial solvency is one of the essential indicators that depict the financial status of a financial institution in general and an insurance institution in particular [40]. Therefore, providing a model that can predict the probability of solvency drop in terms of the effects of internal and external variables can play an effective role in increasing the effectiveness of this index [64]. The supervisory institutions of the insurance market in the world, as the protector of the interests of the insured and the defender of the rights of the victims, continuously control the ability of the insurance institutions to fulfill their obligations. On the other hand, insurers expect the supervisory body of the insurance industry to take necessary measures to protect the rights of policyholders as soon as they see the slightest signs of any crisis. In recent years, insurance supervisory institutions worldwide and other financial institutions have developed EWS early warning systems for careful and preventive monitoring [61].

Early warning systems refer to a structure that identifies and monitors the smallest changes that may lead to a future crisis in an insurance institution, considering various economic, financial, and managerial components [40]. The foundation of these systems is based on estimating the probability of decline and reduction in the ability to fulfill obligations and risks undertaken by the insurance institution. Financial solvency is among the significant indicators representing an insurance company's capacity to meet its long-term financial commitments [67].

Most domestic and international models have attempted to predict the financial solvency of insurance companies using linear models focusing on financial ratios. Financial solvency risks can be divided into internal (managerial and financial ratios) and external (systematic risks and regulatory processes). The issue in assessing the determinants of financial solvency lies in the diversity of theories and the absence of a specific model in the field of factors affecting financial solvency on the one hand and the multiplicity of potential explanatory variables influencing financial solvency on the other, complicating the use of a classic econometric model. One way to overcome the uncertainty in selecting variables and the appropriate model is to use conventional methods in Bayesian econometrics, including the Bayesian Model Averaging (BMA) method. This method tests various models by applying probability rules in modelling and identifies the essential and effective explanatory variables impacting the dependent variable from many potential explanatory variables. Accordingly, the main issue of the present study is modelling the financial solvency of companies listed on the Tehran Stock Exchange. In the second section, the theoretical foundations of the research are presented, which describe the research method of the current topic; the fourth section presents the model estimation results, and the fifth section concludes the paper with a discussion.

2 Theoretical foundations and research background

Company characteristics, financial status, and market information effectively predict a company's financial indicators, including macroeconomic conditions [5]. Many studies have shown that financial and market information effectively predicts financial status. Based on Dimitras et al. [28], it is unclear which financial and market information category should be considered in explaining the models for predicting the financial indicators of the studied companies? Financial indicators are desirable measures for policymakers who wish to evaluate the current state of the economy and predict the future, and are especially important for creditors and the central bank. And there are several reasons to justify this importance. The data based on which the financial indicators are calculated is defined with a view to the future and probably considers the market's expectations regarding big data. Financial indicators may also directly affect the future state of the economy or be affected by micro and macroeconomic indicators [5]. The insurance market is affected by significant internal and external risks, the essential of which are as follows [11]:

A: Global risk: Risks that arise in the natural cycle of development, the global economy, and financial systems, including global financial crises, etc.;

B: Micro and macroeconomic risks, Particularly risks influenced by the decline in national economic growth, reduced investment activity levels, high inflation rates, credit interest rates, low living standards, and insufficient development of domestic infrastructure, etc.;

C: Financial risks: Includes the unsuitable financial condition of a significant portion of insurers and policyholders, low asset levels of insurance companies, investment income dependency on the country's monetary and fiscal policies, etc.;

D: Commercial risks: Risks arising from competitive pricing that have led some companies to the brink of bankruptcy and the growth of unmet obligations, especially in contracts with investment companies, reinsurance companies, banks, etc.

Types of risks affecting financial solvency are presented in Table 1. Financial stress is a condition that leads to the inability of financial institutions to fulfill their obligations and allocate financial resources [23]. In a general sense, financial stress can be defined as a disruption in the normal functioning of the financial market. Furthermore, financial stress leads to the spread of financial instability and damages economic growth and social welfare by disrupting the functioning of the financial system [31, 62]. However, providing a specific and agreed-upon definition is quite challenging, as periods of financial stress are not identical. Financial stress arises from shocks and a vulnerable financial structure. Hence, greater financial fragility (weakness in conditions and financial structure) leads to increased stress [45, 62] and causes a downturn in the economy by increasing the cost of credit and creating uncertainty in financial institutions and investors not only by itself but also by the impact of entering shocks into the market and amplifying it through increased financial loss, risk (increase in the probability of expected loss), and uncertainty in the market [41].

Increased financial stress leads to more significant uncertainty about the value of financial assets, leading to increased volatility in asset prices. Price fluctuations, while making firms more cautious, lead to delays in making important decisions about investment or hiring labor until the uncertainty is resolved [41]. In addition, financial stress leads to banks' adoption of credit standards, thereby reducing economic activity. One of the reasons investors demand a higher return on debt securities or stocks (during financial crises) is that banks are less inclined to lend [41]. Extensive theoretical and empirical studies have been presented in the stress testing of banking and monetary institutions [2, 27]. These studies have attempted to overcome the limitations of stress tests and expand their use in financial sectors. The financial systems of developed countries are under constant evaluation, but developing countries, including Iran, are yet to enjoy such a benefit and are expected to be highly sensitive to economic shocks [57]. Although significant empirical research has been conducted to identify the essential determinants of the level of financial incapacity in financial institutions (such as [7, 9, 51, 78]), there is not much study that investigates this fact using Bayesian models.

Table 1: Risks affecting the financial solvency of insurance companies

Type of variable	**Type of risk**	**position**	**Name of variable**	**Description**
Early warning indicators	Systematic risk	Explanatory	Economic Growth	[4, 22]
		Explanatory	Inflation	[40, 74]
		Explanatory	Inflation uncertainty	[58, 71]
		Explanatory	exchange rate	[52, 54, 58]
		Explanatory	Oil prices	[32, 58]
		Explanatory	Business space	[58, 71]
		Explanatory	Sanctions	[40]
		Explanatory	Globalization index	[15]
		Explanatory	Misery index	[44, 52, 54, 58]
		Explanatory	KOF index	[15, 44]
		Explanatory	Unemployment	[52, 54, 58]
		Explanatory	Foreign direct investment	[58, 71]
	Unsystematic risk	Explanatory	Liquidity ratio	The company's ability to respond to short-term liabilities [73, 78].
		Explanatory	Current ratio	Coverage of current assets by current liabilities [73, 78].
		Explanatory	Return on working capital	Net profit divided by working capital [73, 57].
		Explanatory	Measuring the Loan Usefulness	Return on capital divided by return on assets [73, 78].
		Explanatory	Return on capital ratio	Net profit divided by equity [73, 74]
		Explanatory	Quick Ratio	Total current assets minus inventory and prepayments [78]
		Explanatory	Return on assets	Net profit before tax divided by average assets [73, 78]
		Explanatory	Current asset ratio	Dividing current assets into total assets [57, 73, 78]

		Explanatory	Cash adequacy ratio	Dividing cash from operations by the sum of divided cash profits [57, 73, 78].
		Explanatory	Cash turnover ratio	Cash flow from operations on current liabilities [73, 78].
		Explanatory	Net working capital	The difference between its current liabilities and assets [57, 73, 78].
		Explanatory	Debt Ratio	Dividing the sum of current assets by the sum of assets [73, 74]
		Explanatory	Total debt to equity ratio	Total debt, both current and long-term, on equity [73, 74]
		Explanatory	Proprietary ratio	Equity divided by total assets [73, 57]
		Explanatory	Long-term Debt to Equity Ratio	Equity divided by long-term debt [73, 78]
	Monitoring indicators	Explanatory	Issued Gross Premium to Surplus	$\frac{\text{Gross insurance premiums issued}}{\text{surplus}} \times 100$
		Explanatory	Net Premium to Surplus	$\frac{\text{Net premium issued}}{\text{surplus}} \times 100$
		Explanatory	Change in Issued Net Premium	$\frac{\text{Net premium issued last year} - \text{Net premiums issued for the current year}}{\text{Net premium issued last year}} \times 100$
		Explanatory	Surplus Assistance (via Reinsurance) to Surplus	$\frac{\text{Reinsurance fee}}{\text{Reinsurance premium}} - \text{Reinsurance fee ratio}$
		Explanatory	Two-Year Operational Ratio	2-year cost factor + 2-year damage factor + 2-year investment income factor
		Explanatory	return on investment	$\frac{\text{Earned investment income}}{\text{Average cash and assets of current and previous year's investments}} \times 100$
		Explanatory	Gross Change in Surplus	$\frac{\text{Change in surplus}}{\text{Last year's surplus}} \times 100$
		Explanatory	Change in Adjusted Surplus	$\frac{\text{adjusted surplus}}{\text{Last year's surplus}} \times 100$
		Explanatory	Adjusted Liabilities to Current Assets	$\frac{\text{Adjusted liabilities}}{\text{Current assets}} \times 100$
		Explanatory	Gross Agents' Balance (Total) to Surplus	$\frac{\text{Gross balance of representatives in total}}{\text{surplus}} \times 100$
		Explanatory	Increase in One-Year Reserve to Surplus	$\frac{\text{Increase one}-\text{year loss reserve}}{\text{Last year's surplus}} \times 100$
		Explanatory	Increase in Two-Year Reserve to Surplus	$\frac{\text{Increase the two}-\text{year loss reserve}}{\text{The surplus of the last two years}} \times 100$
		Explanatory	Shortfall of Current Estimated Reserve to Surplus	$\frac{\text{Shortfall (surplus) of estimated damage reserve and cost of damage assessment}}{\text{surplus}}$
Financial Solvency		Dependent	Financial Solvency	Required capital divided by available capital [57]

In the following, the research background has been examined.

[40] provided a model of an early warning system of financial wealth for insurance companies, especially companies active in Iran's insurance market. The experimental model of the research was fitted using the econometric method with the combined data approach (panel) for 18 companies active in the insurance market of Iran in 2008-2017. The findings showed that the bank interest rate with a break period and the board of directors change had the most and the least effect on the financial prosperity of the mentioned insurance companies, respectively. In addition, the damage coefficient was different in different values due to being the third power. All the assumptions of the article regarding the significance of the impact of macroeconomic variables (inflation rate (with one break), bank interest rate (with one break), economic growth (with one break)), corporate variables (the ratio of investment in risky assets to total assets, loss ratio, and Herfindahl-Hirschman field index), and corporate governance (percentage of shares owned by the major shareholder and the ratio of board member changes) as well as international economic sanctions on the wealth of Iranian insurance companies were confirmed.

[3] identified the effects of efficiency and financial risk, including credit, operational, liquidity, and solvency, on the performance of insurance companies. The research sample data comprised 13 insurance companies on the Tehran Stock Exchange from 2013-2017. The results indicated a significant relationship between performance and credit, liquidity, operational risks, and financial solvency. Moreover, the findings demonstrated a significant and direct correlation between efficiency and appropriate types of performance.

[64] developed an early warning system model based on the probability of solvency decline from its critical value from the insurance regulator's perspective for Iranian insurance companies. The logistic panel econometrics method fits the early warning model with data from 18 insurance companies in 2008-2017. The findings indicated that financial variables included the current ratio, Herfindahl-Hirschman Index for industry concentration, and loss ratio, and economic variables contained bank interest rates, economic growth, and international economic sanctions, and corporate governance variable changes in the board of directors as predictors of the probability of financial solvency

falling to a critical level (solvency level 2 and below). Bank interest rates and changes in the board of directors had the most and least impact, respectively, while the loss ratio had the most significant effect at higher values.

[73] presented a predictive model for the financial solvency of insurance companies by examining the history of 17 variables as predictors for forecasting the financial solvency class, extracted from reliable sources on the Central Insurance of Iran website from 2013 to 2017. Initially, the results from applying various prediction models based on artificial intelligence including Decision Tree, Neural Network, and Naive Bayes were compared. Subsequently, the ranking of the predictive algorithms was examined. The findings revealed that the Decision Tree, with an accuracy of 99%, performed best in predicting financial solvency, given that the Decision Tree maps non-linear cognitive and chaotic patterns between target variables and decisions.

[56] investigated the presentation of a model for the risks in Iran's insurance industry. To this end, Grounded Theory (GT) and structural equation modeling (SEM) were used. The data needed for the research was collected through in-depth interviews with several prominent experts and researchers in the insurance industry, as well as questionnaires. As a result of the open coding of the interviews, 97 concepts were identified, which were the strategic management risks of Iran's insurance industry in the form of the following after classification: commercial (environmental) risks, organizational risks, operational (process) risks, technical risks, knowledge risks, human resource risks, and event risk. The validity of the designed model was also confirmed through structural equation modeling.

[25] designed an early warning system model comprising macroeconomic and firm-specific financial indicators for European insurance companies. The model, estimated using a sample of 36 insurance companies, employed the binomial logit panel for estimation. Results indicated that economic growth, inflation, and interest rates adversely affected the solvency of insurance companies. At the corporate level, a decrease in asset returns and the book-to-market value ratio, as well as operational costs, were impactful on the financial solvency of insurance companies.

[74] assessed the effects of the financial insolvency of insurers on their profitability, employing return ratios, Return on Assets (ROA), and Return on Equity (ROE) using panel data from 2011-2019 of 16 non-life insurance companies in Bangladesh. Regression results signify that financial insolvency significantly negatively impacts the profitability of non-life insurance companies. Further findings indicated that financial leverage, age, and inflation significantly negatively affected insurance companies' profitability.

Kristanti et al. [50] addressed the determinants of financial stress in Indonesian insurance companies as an early warning system for the firms. Logistic regression results revealed that premium growth and company size negatively impact financial solvency. Claim costs, liquidity, debt payment margin, and business cycles did not significantly affect financial solvency.

[1] explored the impact of liquidity, investment, leverage, and losses on the financial solvency of seven insurance companies during 2010-2017 using fixed effects panel regression. They concluded that the loss ratio had a positive effect, whereas leverage (debt to financial assets ratio) had a negative impact on the financial solvency of Palestinian insurance companies. Investments and liquidity did not significantly influence financial solvency.

In summarizing the theoretical foundations and literature review, numerous studies nationally and internationally have examined the factors affecting financial solvency using stress testing in insurance companies. However, this research differs in two aspects from others and concurrently examines the impact of both systematic and unsystematic, as well as regulatory risks on financial solvency in insurance companies using an averaging model. Secondly, the effects of over 40 risks on the financial solvency of insurance companies are examined in three main categories. Based on the results of the study's theoretical foundations, literature review, and estimation approach, the research conceptual model is depicted in Figure 1.

3 Research method

This applied and analytical study aimed to solve the problem related to this research due to its reliance on theoretical bases and research precedents. From the perspective of the logic of implementation (or type of reasoning), the present research is inductive, as it attempts to demonstrate the relationship between financial solvency variables and three other variables through the collection of data from the Central Bank, Statistical Center, registered financial statements, and statistical reports of the Central Insurance of Iran. The research is longitudinal (retrospective) from the temporal dimension perspective because the data under study are collected and analyzed over time (several years). This research is conducted in the present but utilizes data from the previous year to examine the relationship between variables. The population of this research is the Iranian insurance industry. The sample is selected based on the purposive method from insurance companies active in Iran's capital market within the mentioned time frame, chosen

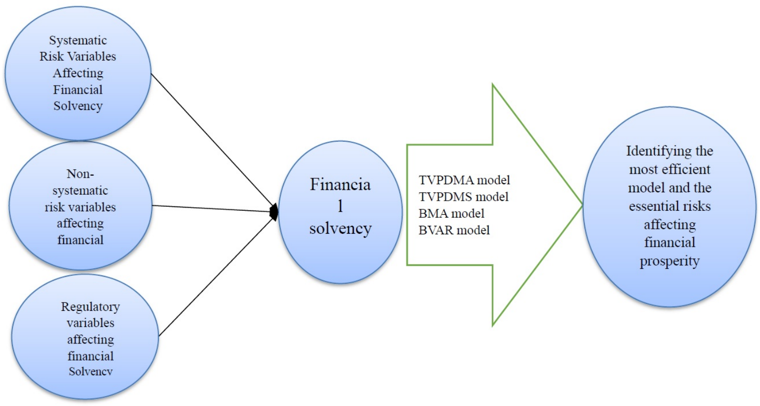


Figure 1: Research conceptual model (The list of each of the variables of the relevant factors is presented in Table 1.)

for their accessible information. The timeframe for the present research spans from 2006 to 2020. The methods employed in this research are presented in the continuation.

3.1 Time-Varying parameters dynamic model averaging and time-varying parameters dynamic model selecting methods (TVP-DMA and TVP-DMS)

The standard form of state-space models is as follows:

$$\begin{aligned} y_t &= z_t\theta_t + \epsilon_t \\ \theta_t &= \theta_{t-1} + \mu_t \end{aligned} \tag{3.1}$$

In which, y_t is a dependent variable, $z_t = [1, x_{t-1}, y_{t-1}, ..., y_{t-p}]$ presents a $1 \times m$ vector of estimators of the explanatory variable of the model and $\theta_t = [\varphi_{t-1}, \beta_{t-1}, \gamma_{t-1}, ..., \gamma_{t-p}]$ indicates an $m \times 1$ vector of coefficients (states). The values of $\varepsilon_t \sim N(0, H_t)$ and $\mu_t \sim (0, Q_t)$ have a normal distribution with zero mean and variance of H_t and Q_t, respectively. These models have many advantages, the main of which is that they can change the estimated coefficients at any moment, but their disadvantage was that when z_t became too large, the estimates would not be very reliable. Generalized TVP models such as TVP-VAR have the same problems. This model, including the uncertainty of women's estimation behavior, is as follows:

$$y_t = \sum_{j=1}^{m} s_j\theta_{jt}z_{jt} + \varepsilon_t \tag{3.2}$$

in which, θ_{jt}, z_{jt}, and j^{th} are the j^{th} elements of θ_t and z_t. The point added to their model is the variable $s_j \in \{0, 1\}$ which cannot change over time and only has the status of a permanent variable that can accept the number one or zero for each estimator [44]. Next, Raftery [66] presents the DMA method, which overcomes all the limitations of the previous methods. This method could estimate massive models and allow the input variables to be changed at any moment. Describing the DMA method is based on assuming K sub-set models of z_t variables as estimators and $z^{(k)}$ with $k = 1, 2, ..., K$ represents the above K sub-set models. Thus, assuming the existence of K subset models at each point in time, the state-space model is described as follows:

$$\begin{aligned} y_t &= z_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)} \\ \theta_{t+1}^{(k)} &= \theta_t^{(k)} + \mu_t^{(k)} \end{aligned} \tag{3.3}$$

$\varepsilon_t^{(k)} \sim N(0, H_t^{(k)}), \mu_t^{(k)} \sim (0, Q_t^{(k)})$, and $\vartheta_t = (\theta_t^{(1)}, ..., \theta_t^{(k)})L_t \in \{1, 2, ..., K\}$ indicates that each model out of K models in the subset is better used at which time point, which allows estimating a different model at any moment is called the dynamic averaging model [47]. Regarding the difference between DMA and DMS dynamic models in predicting a variable at time t based on t-1 information, it can be said that the DMA model includes the calculation of $Pr(L_t = k|y^{t-1})$ with $L_t \in \{1, 2, ..., K\}$ and averaging the predictions of the models is based on the above probability. However, DMS includes selecting a model with the highest probability $Pr(L_t = k|y^{t-1})$ and predicting the model with the highest probability.

3.2 Bayesian econometric approach

A distinctive characteristic of the Bayesian approach to inference is assigning numerical probabilities to a researcher's degree of belief; however, the extent of a researcher's belief in the validity of a hypothesis depends on the information at that moment. For instance, in this method, the researcher introduces n variables as the most significant variables affecting the dependent variable in the Bayesian averaging model based on mastery of the subject, the relationship between variables, and the conditions of the country under study. When the researcher's viewpoint is correct, the output results confirm their perspective. For example, eight variables is identified as factors influencing economic growth in America, and the model's output results were consistent with the researcher's viewpoint. Therefore, with a change in information about a statement, a reconsideration of the probability related to the accuracy or inaccuracy of the said statement must also take place [48]. The revising process in probabilities through new information, denoted by y, is briefly illustrated below [79].

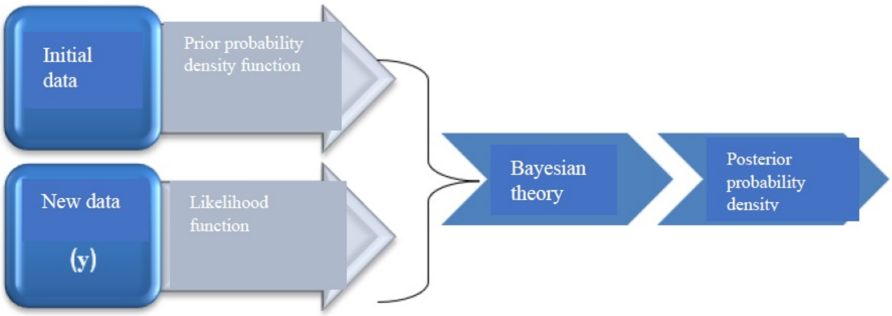


Figure 2: Bayesian model averaging (The Bayesian averaging method is based on the conditional probability approach. Primary information means the number of data based on which the prior data distribution is extracted. New observations are the number of data added to the model after estimating the prior distribution, which extracts the posterior distribution based on the prior distribution information (conditional probability discussion).)

The prior probability density function related to hypothesis H is based on preliminary information, which typically consists of a combination of prior data, empirical studies, observations, and theories. The posterior probability density function for new observations, y, given hypothesis H, is known as the likelihood function. The prior probability density function must be combined with the likelihood function through Bayesian theory to obtain the posterior probability density function. The posterior probability depends on the prior information, I_0, and the sample data, y, and is reshaped from the prior probability density function to the posterior probability density function by the impact of new data information through Bayesian theory. The posterior probability encompasses the researcher's view of the parameter, data information, and prior information [29]. Prior information enters the posterior probability function through the prior probability function, and sample information enters through the likelihood function. The posterior probability function is used for inference about variables in the Bayesian approach. Prior probability density functions can take various forms, such as normal, depending on the research context. The prior probability distribution function parameters are determined based on the researcher's opinion. When the prior information is derived from existing information in past samples, such probability density functions are called data priors. In other cases, prior information comes from observed cause-and-effect relationships, theoretical discussions, or sources other than existing samples from past data. When a prior probability density function is based on this type of information, it is referred to as non-data prior information, and the probability density functions are called non-data priors. When non-data priors are used due to the unavailability of past data, these non-data pieces of information might be very vague and imprecise. When a researcher wishes to ascertain how new sample information improves knowledge about model parameters and the initial information is non-data, they must use a non-data prior probability density function combined with a likelihood function to obtain the posterior probability density function. Comparing the non-data prior probability density function with the posterior probability density function allows observing how new sample data information revises initial beliefs about the non-data information [48, 79].

3.3 Vector autoregressive models and Bayesian vector autoregression

In time series models, the degree of freedom decreases by two units for each interval increase (due to the coefficient of the intermittent variable and the loss of an effective observation), significantly reducing the degree of freedom in the VAR equation system. Therefore, with the increase of intervals in the VAR model or the number of variables, statistical inference faces problems. A way to increase the accuracy of the statistical inference of this model is to use the Bayesian estimation method, presented here as the Litterman approach, also known as the Minnesota approach. A family of Minnesota ancestors based on the assumption that $\sum_{\varepsilon}$ is known, and by replacing $\widehat{\sum_{\varepsilon}}$, this assumption will simplify extracting the prior and calculating the posteriors. There are typically three choices of estimator $\sum_{\varepsilon}$.

Univariate AR: $\widehat{\sum_{\varepsilon}}$ in this case is limited to the diagonal matrix. $\widehat{\delta}^2_{ii}$ is the element of the i-th row and i-th column of the matrix $\widehat{\sum_{\varepsilon}}$, which is calculated using the OLS method of the AR variance of its i-th variable.

Full VAR: In this case, classical VAR estimates are used for $(\widehat{\sum_{\varepsilon}})$.

Diagonal VAR: $\widehat{\sum_{\varepsilon}}$ In this case, it is bound to the diagonal matrix. The diagonal elements of the matrix are obtained using the full VAR system (in this case, the off-diagonal elements are assumed to be zero).

Since $\sum_{\varepsilon}$ is replaced by $(\widehat{\sum_{\varepsilon}})$, in the Bayesian estimation of the VAR system, it is only necessary to specify the prior distribution function of the coefficients θ. In the definition of the prior distribution of θ, Litterman assumes that $(\theta_0 = 0, \theta \sim N(\theta_0, V_0))$ using the superparameter $\mu_1 = 0$, which states that the mean of the model is equal to zero, it is assumed that $V_0 \neq 0$. Any value for μ_1 is theoretically possible when choosing a mean value of zero risk overfitting. For the previous explanation of covariance V_0 Minnesota/Litterman, the explanatory variables in each equation of the VAR system are divided into three groups of explanatory variables with an interval of the dependent variable, an interval of other dependent variables, and exogenous variables, including the constant term. The elements of V_0 corresponding to the exogenous variables are a set containing infinity. What remains is about the diagonal elements of the matrix V_0, denoted by the symbol v^l_{ii} for $l = 1, 2, ..., p$.

$$v^l_{ii} = \left\{ \begin{array}{ll} \left\{\frac{\lambda_1}{l^{\lambda_3}}\right\}^2, & \text{for}(i = j) \\ \left\{\frac{\lambda_1 \lambda_2 \sigma_i}{l^{\lambda_3} \sigma_j}\right\}^2, & \text{for}(i \neq j) \end{array} \right\} \tag{3.4}$$

in which, σ^2_i is the ith diagonal element of the matrix $\sum_{\varepsilon}$. This way of choosing the former makes the calculation simpler. Changes in the values of these parameters may lead to smaller or larger variance coefficients. The posterior density for the parameter θ is obtained for selecting the prior function. The primary advantage of the Minnesota/Litterman prior is that it leads to simple a priori inference [43].

$$\theta : N(\overline{\theta}, \overline{V}) \tag{3.5}$$

in which

$$\overline{V} = [V_0^{-1} + (\widehat{\sum_{\varepsilon}^{-1} \bigotimes \acute{X} X})]^{-1} \tag{3.6}$$

$$\overline{\theta} = \overline{V}[V_0^{-1}\theta_0 + (\widehat{\sum_{\varepsilon}^{-1} \bigotimes X})y]^{-1} \tag{3.7}$$

Bayesian inference derives from Bayes' theorem, introduced by Thomas Bayes (1702-1761). Bayesian inference is utilized for evaluating financial and economic hypotheses, estimating economic parameters, and predicting variables previously unobserved, addressing numerous crucial issues in decision-making, control and policy matters, economic optimization problems for consumers and producers, asset allocation issues, and experimental design, among other applications [79]. Bayes' theorem significantly allows prior information combined with current sample data to obtain posterior information [57]. The BVAR model complements the system of simultaneous equations, and the vector autoregression model is constructed dynamically based on theory in the system of simultaneous equations [6]. Bayesian models have three fundamental components: the prior density function, the likelihood function, and the posterior density function. Given that the model's outcomes vary depending on the type of prior used, selecting an appropriate prior in Bayesian models is critically important. Various priors have been employed in Bayesian vector autoregression models, the most notable being the Minnesota prior, first introduced by [13, 53, 75]. The unrestricted vector autoregression model with n equations and ρ lags, denoted as $VAR(\rho)$, can be expressed as equation (3.8).

$$\acute{y}_t = \acute{z}_t C + \sum_{j=1}^{\rho} \acute{y}_{t-j} A_j + \acute{\varepsilon} \qquad t = 1, 2, .., T \tag{3.8}$$

in which, y_t is $n \times 1$ vector, including dependent variables, z_t is $h \times 1$ vector of fixed components and exogenous variables, C and A_j are respectively $h \times n$ and $n \times n$ matrix of model coefficients and ε_t is error component vector.

In such a way that $\varepsilon_t^{iid} \sim N_n(0, \sum \cdot)$ is assumed. The variance-covariance matrix $\sum 0$ is also a positive definite and unknown matrix with $n \times n$ dimensions. By defining the vector $\acute{x}_t = (\acute{z}_t, \acute{y}_{t-1}, ..., \acute{y}_{t-p})$, the model presented in Equation (3.8) can be rewritten as Equation (3.9):

$$Y = AX + \varepsilon \tag{3.9}$$

As in Equation (3.10), the Y matrix is defined so that its dimensions are $T \times n$ and all observed T related to each dependent variables are shown in separate columns [69].

$$Y = \begin{bmatrix} \acute{y}_1 \\ \vdots \\ \acute{y}_p \end{bmatrix}, \quad X = \begin{bmatrix} \acute{x}_1 \\ \vdots \\ \acute{x}_p \end{bmatrix}, \quad A = \begin{bmatrix} C \\ A_1 \\ \vdots \\ A_p \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \acute{\varepsilon}_1 \\ \vdots \\ \acute{\varepsilon}_p \end{bmatrix} \tag{3.10}$$

4 Model estimation

4.1 Bayesian and dynamic averaging model estimation

In recent decades, a segment of the financial literature has scrutinized the requisite information volume for obtaining a robust forecast of economic and financial variables [19, 20, 24, 35, 55]. A significant achievement in this area has been applying various econometric methods to utilize big data information for forecasting purposes. In such an approach, factor models have garnered significant attention, becoming increasingly common. Factor models condense information from a vast array (big data) of indices into a few fundamental, unobservable components.

Studies by [8, 10, 37, 55, 72, 76, 77] , serve as examples of empirical research employing factor models. Extracting information from big data can significantly enhance the forecasting process, with initial outcomes from forecasting in empirical studies proving highly promising [36, 59, 76, 77], which forecasted macroeconomic variables of the United States utilizing over 215 variables. Time-varying parameter (TVP) models employing state-space methods (such as the Kalman filter) are generally used for structural analysis and forecasting in experimental macroeconomic research. When a large dataset is employed for forecasting macroeconomic variables, TVP models tend to overfit within the sample, hence exhibiting poor forecasting performance out-of-sample. DMS and DMA models were utilized to mitigate these shortcomings in TVP models [12]. Given that DMS and DMA models depend on the past values of coefficients and probabilities, studies below that have exploited these values are referred.

Table 2: Values (α, λ) in the models of DMS and DMA models

α and λ values	**Researchers**
$(\alpha = 0.95, \lambda = 1)$	[34, 39, 49]
$(\alpha = 1, \lambda = 1)$	[14, 46, 47]
$(\alpha = 0.99, \lambda = 1)$	[21, 33, 46, 47, 59]
$(\alpha = \lambda = 0.99)$	[12, 17, 30, 33, 34, 47, 59, 60, 66, 68, 70]
$(\alpha = \lambda = 0.95)$	[16, 17, 30, 33, 34, 47, 60, 63, 70]
$(\alpha = \lambda = 0.90)$	[16, 30, 63]

In the following, the results of applying different α and λ are presented to explain the optimal model.

Table 3: Forecast performance criteria in different forecast horizons

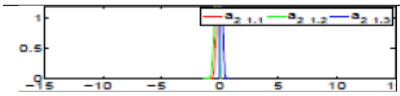
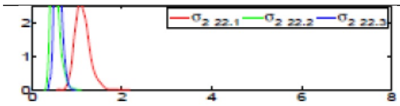
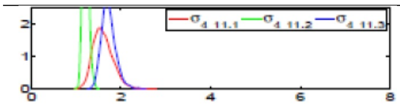
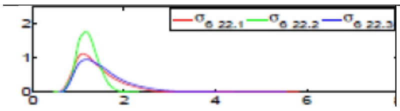
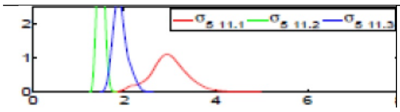
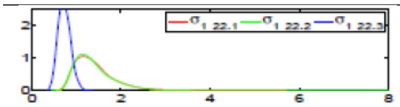
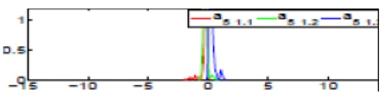
Forecast period		**h=1**					
		Log(PL)	**MAFE**	**MSFE**	**MAPE**	**FEV**	**Bias**
$TVP-AR(1)-X$	$DMA(\alpha = \lambda = 0.99)$	73.36	0.0752	0.0101	0.1987	0.0098	0.0178
$TVP-AR(1)-X$	$DMA(\alpha = \lambda = 0.95)$	81.18	0.0658	0.0077	0.1947	0.0074	0.0154
$TVP-AR(1)-X$	$DMA(\alpha = \lambda = 0.90)$	82.98	0.0602	0.0067	0.1789	0.0065	0.0142
$TVP-AR(1)-X$	$DMS(\alpha = \lambda = 0.99)$	74.19	0.0810	0.0113	0.2030	0.0110	0.0192
$TVP-AR(1)-X$	$DMS(\alpha = \lambda = 0.95)$	85.62	0.0708	0.0087	0.1800	0.0085	0.0118
$TVP-AR(1)-X$	$DMS(\alpha = \lambda = 0.90)$	106.70	0.0560	0.0061	0.1613	0.0059	0.0157

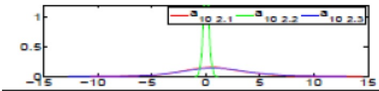
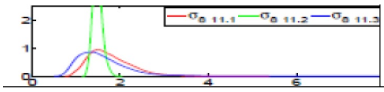
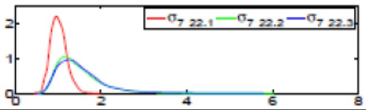
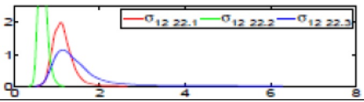
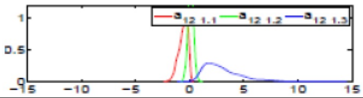
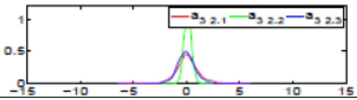
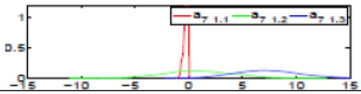
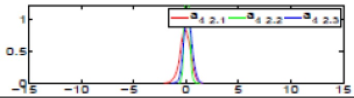
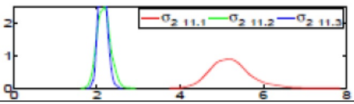
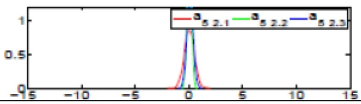
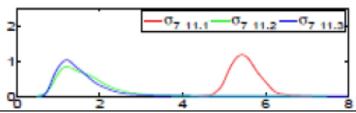
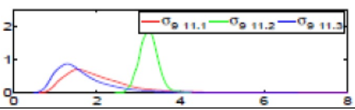
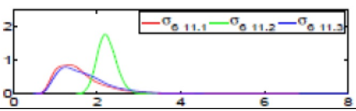
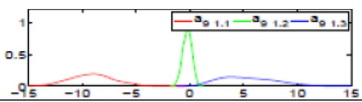
$TVP-AR(1)-X$	$DMA(\alpha=0.99,\lambda=1)$	70.85	0.0773	0.0102	0.2067	0.0099	0.0172
$TVP-AR(1)-X$	$DMA(\alpha=0.95,\lambda=1)$	75.58	0.0711	0.0081	0.2351	0.0075	0.0243
$TVP-AR(1)-X$	$BMA(\alpha=\lambda=1)$	116.7	0.0147	0.0023	0.1123	0.0221	0.0048
$BVAR-Minnesota$		–	0.500	0.341	0.761	0.117	0.473
$TVP-AR(1)-X$	$DMA(\lambda=0.99)$	–	0.0831	0.0119	0.2430	0.0109	0.0317
$TVP-AR(1)-X$	$DMA(\lambda=0.95)$	–	0.0878	0.0130	0.2240	0.0122	0.0287
$AR(1)-XOLS$		–	0.1061	0.0186	0.3235	0.0161	0.0492
$AR(1)(OLS)$		–	0.1416	0.0304	0.4638	0.0182	0.1106
Forecast period				**h=4**			
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.99)$	69.49	0.0791	0.0109	0.1943	0.0105	0.0208
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.95)$	76.76	0.0662	0.0078	0.1823	0.0076	0.0162
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.90)$	78.05	0.0606	0.0068	0.1699	0.0066	0.0149
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.99)$	69.59	0.0841	0.0121	0.1990	0.0116	0.0216
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.95)$	79.87	0.0723	0.009	0.1775	0.0089	0.0100
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.90)$	97.92	0.0609	0.0071	0.1709	0.007	0.0100
$TVP-AR(1)-X$	$DMA(\alpha=0.99,\lambda=1)$	67.06	0.0789	0.0106	0.197	0.010	0.016
$TVP-AR(1)-X$	$DMA(\alpha=0.95,\lambda=1)$	73.10	0.070	0.007	0.206	0.007	0.022
$TVP-AR(1)-X$	$BMA(\alpha=\lambda=1)$	99.25	0.0174	0.0029	0.1054	0.0026	0.0151
$BVAR-Minnesota$		–	0.514	0.389	1.096	0.153	0.486
$TVP-AR(1)-X$	$DMA(\lambda=0.99)$	–	0.106	0.036	0.426	0.034	0.036
$TVP-AR(1)-X$	$DMA(\lambda=0.95)$	–	0.093	0.031	0.375	0.030	0.031
$AR(1)-XOLS$		–	0.109	0.019	0.315	0.017	0.048
$AR(1)(OLS)$		–	0.147	0.032	0.435	0.019	0.115
Forecast period				**h=8**			
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.99)$	65.44	0.081	0.011	0.549	0.011	0.011
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.95)$	72.49	0.066	0.007	0.402	0.007	0.013
$TVP-AR(1)-X$	$DMA(\alpha=\lambda=0.90)$	73.55	0.060	0.006	0.317	0.006	0.014
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.99)$	63.3	0.085	0.012	0.552	0.012	0.010
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.95)$	76.27	0.076	0.011	0.460	0.010	0.009
$TVP-AR(1)-X$	$DMS(\alpha=\lambda=0.90)$	90.7	0.065	0.008	0.428	0.008	0.012
$TVP-AR(1)-X$	$DMA(\alpha=0.99,\lambda=1)$	67.21	0.078	0.010	0.568	0.010	0.011
$TVP-AR(1)-X$	$DMA(\alpha=0.95,\lambda=1)$	72.55	0.066	0.007	0.473	0.006	0.013
$TVP-AR(1)-X$	$BMA(\alpha=\lambda=1)$	83.25	0.017	0.002	0.079	0.005	0.002
$BVAR-Minnesota$		–	0.336	0.197	0.911	0.187	0.096
$TVP-AR(1)-X$	$DMA(\lambda=0.99)$	–	0.099	0.141	3.64	0.102	0.199
$TVP-AR(1)-X$	$DMA(\lambda=0.95)$	–	0.093	0.083	2.55	0.083	0.089
$AR(1)-XOLS$		–	0.103	0.017	0.895	0.016	0.037
$AR(1)(OLS)$		–	0.146	0.032	1.025	0.019	0.111

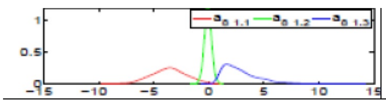
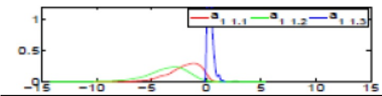
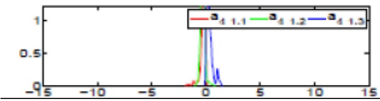
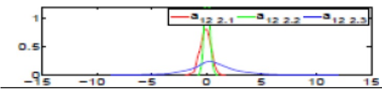
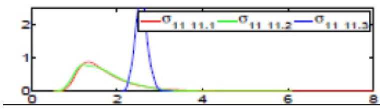
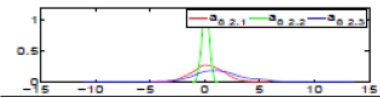
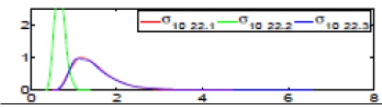
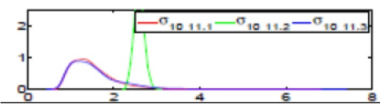
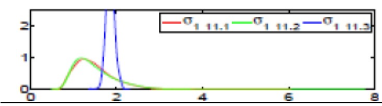
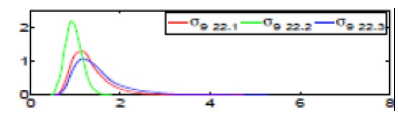
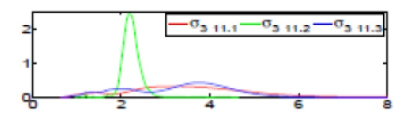
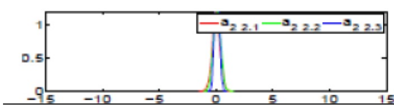
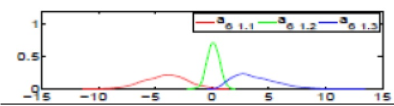
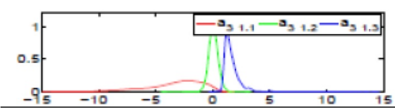
The results showed that the BMA model performs better in all modes. According to Table 3 and using the maximum right-hand exponential index (Log(PL)) indicating the accuracy of the estimated model, the optimal model is the Bayesian averaging approach in three time periods: h=1, 4, and 8. In examining the results of the BMA model, first, all the possible modes of presence of explanatory variables are regressed on the dependent variable. First, one variable is not present in all feasible models. Second, the mentioned variable does not necessarily significantly affect the dependent variable in all the present models. The ratio of the number of models in which the variable is significant to the number of models in which it is present is an indicator of the presence of the variable in the optimal model. Third, it is impossible to calculate all modes with the increased number of variables. After several estimations (about 100 to 200 million regressions), the ratio of the significant presence of a variable to all states tends to a specific number, and there is no need to estimate all states. Finally, there is a need for a decision threshold to eliminate variables. The ratio of k divided by the total variables has been used to determine the optimal limit (k is the number of proposed variables that have the highest impact on the dependent variable from the researcher's point of view). This k is experimental and chosen based on the researcher's point of view. Calculations should be done on all the models in the model space to reach the result. According to the number of investigated variables, the number of available models (based on the presence or absence of each variable) in the model space equals 240 models, more than 1099 billion regression models (1,099,511,627,776 is the exact number of possible states with 40 explanatory variables. MATLAB

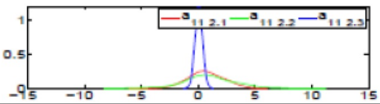
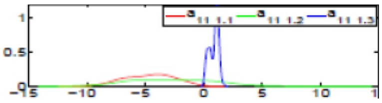
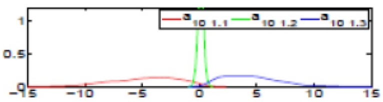
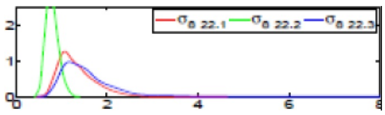
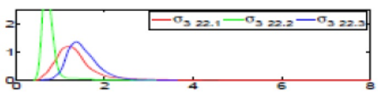
BMA code was used in MATLAB 2021 software space due to the high number of estimated models.). In other words, the model space contains 240 models, all models should be examined, and the information of all models should be used to reach the result, according to the assumption of model uncertainty, that is, away from applying personal opinion in model selection. The value of k in this research is considered equal to 10, i.e., Finally, ten variables are introduced as non-fragile variables by the calculation process. It is quite clear that having less or more than ten non-fragile variables is possible. Each variable's coefficients and posterior probability were calculated in MATLAB software version 2021, first by obtaining a sample containing 1 million regressions from the model space. Next, 1 million regressions were added to the first sample, calculations were made for 2 million regressions, and coefficients and posterior probabilities were obtained. Convergence was achieved by continuing this process in a sample that included 5 million regressions. Thus, there is no need to increase the sample size to determine non-fragile variables (Table 4). Two conditions should be fulfilled to introduce a variable as non-fragile: 1) An increase in the posterior probability of each variable compared to the prior probability. 2) The posterior probability level is higher than the defined threshold level ("initial threshold level = 12 divided by 40 = 0.30"). In the first stage, non-data information was used due to the assumption of uncertainty in the model. In the second stage, data information was utilized to achieve convergence faster. The variables whose posterior probability was considered lower than the prior probability were removed from the model due to being fragile compared to other variables (In the first stage, there were 23 non-fragile variables, and in the second stage, the calculations were continued with these variables, which have a higher posterior probability than the previous probability).

Table 4: The first stage of the sampling process and calculations assuming $\overline{K} = 12$

Bayesian averaging charts	**The first sample contains 5 million regressions**		**The first sample contains 1 million regressions**		**Variable**
	Posterior probability	**Posterior coefficient**	**Prior probability**	**Prior coefficient**	
	0.321	0.132	0.207	0.032	Economic Growth
	0.092	0.003	0.073	0.004	Inflation
	0.546	0.023	0.170	0.024	Inflation uncertainty
	0.478	0.176	0.235	0.319	exchange rate
	0.269	0.127	0.145	0.417	Oil prices
	0.455	0.209	0.318	0.428	Business space
	0.694	0.788	0.407	0.147	Sanctions

	0.381	0.034	0.270	0.029	Globalization index
	0.588	0.051	0.407	0.080	Misery index
	0.222	0.068	0.199	0.111	KOF index
	0.247	0.400	0.122	0.093	Unemployment
	0.241	0.007	0.222	0.006	Foreign direct investment
	0.461	0.127	0.102	0.599	Liquidity ratio
	0.362	0.022	0.130	0.039	Current ratio
	0.319	0.718	0.179	0.692	Return on working capital
	0.230	0.025	0.173	0.015	Measuring the Loan Usefulness
	0.525	0.000	0.252	0.016	Return on capital ratio
	0.290	0.188	0.138	0.059	Quick Ratio
	0.412	0.955	0.162	0.489	Return on assets
	0.195	0.044	0.190	0.189	Current asset ratio
	0.428	0.000	0.109	0.039	Cash adequacy ratio

	0.218	0.546	0.123	0.129	Cash turnover ratio
	0.279	0.014	0.205	0.017	Net working capital
	0.698	0.034	0.106	0.002	Debt Ratio
	0.796	0.031	0.691	0.060	Total debt to equity ratio
	0.283	0.020	0.164	0.034	Proprietary ratio
	0.492	0.057	0.317	0.187	Long-term Debt to Equity Ratio
	0.243	0.002	0.073	0.002	Issued Gross Premium to Surplus
	0.198	0.000	0.239	0.102	Net Premium to Surplus
	0.195	0.007	0.122	0.006	Change in Issued Net Premium
	0.527	0.013	0.302	0.006	Surplus Assistance (via Reinsurance) to Surplus
	0.132	0.216	0.230	0.394	Two-Year Operational Ratio
	0.529	0.001	0.157	0.002	return on investment
	0.230	0.025	0.273	0.015	Gross Change in Surplus
	0.214	0.188	0.073	0.059	Change in Adjusted Surplus

	0.644	0.721	0.180	0.721	Adjusted Liabilities to Current Assets
	0.131	0.366	0.108	0.346	Gross Agents' Balance (Total) to Surplus
	0.233	0.044	0.190	0.189	Increase in One-Year Reserve to Surplus
	0.240	0.204	0.160	0.203	Increase in Two-Year Reserve to Surplus
	0.165	0.366	0.132	0.346	Shortfall of Current Estimated Reserve to Surplus

All the steps performed in the first step were applied to the remaining 23 variables in the second step. In the second step, a sample containing 1 million regressions was applied to 23 selected variables, and coefficients and posterior probabilities were calculated. In the following, the essential variables affecting financial wealth were identified using the two mentioned conditions: "secondary threshold level = 12 divided by 23 = 0.521". The results can be observed in Table 5.

Table 5: The second stage of the sampling process and calculations assuming $\overline{K} = 12$

Variable	**The first sample contains 1 million regressions**		**The first sample contains 2 million regressions**	
	Prior coefficient	**Prior probability**	**Posterior coefficient**	**Posterior probability**
Economic growth	0.036	0.232	0.148	0.560
Inflation uncertainty	0.027	0.190	0.026	0.612
Exchange rate	0.357	0.263	0.197	0.535
Oil price	0.467	0.162	0.142	0.301
Business space	0.479	0.356	0.234	0.510
Sanctions	0.165	0.456	0.883	0.777
Globalization index	0.032	0.302	0.038	0.427
Misery index	0.090	0.456	0.057	0.459
Liquidity ratio	0.671	0.114	0.142	0.576
Current ratio	0.044	0.146	0.025	0.405
Return on working capital	0.775	0.200	0.804	0.657
Return on capital ratio	0.018	0.282	0.000	0.788
Quick Ratio	0.066	0.155	0.211	0.325
Return on assets	0.548	0.181	1.070	0.461
Cash adequacy ratio	0.044	0.122	0.000	0.479
Net working capital	0.019	0.230	0.016	0.312
debt ratio	0.002	0.119	0.038	0.782
Total debt to equity ratio	0.067	0.774	0.035	0.892
Proprietary ratio	0.038	0.184	0.022	0.317
The ratio of long-term debt to equity	0.209	0.355	0.064	0.551

Surplus contribution (through reinsurance) to Surplus	0.007	0.338	0.015	0.590
return on investment	0.002	0.176	0.001	0.592
Adjusted liabilities to current assets	0.808	0.202	0.808	0.721

In total, 13 variables were selected in the second step using conditions to determine non-fragile variables. In other words, 13 variables had a higher posterior probability value than the prior probability with a posterior probability level higher than the threshold level of 0.5217.

Upon the computational K is very close to the proposed K, calculations ceased (if the difference between the proposed K and the resulting K is less than 10%, researchers may use the K obtained from the model). The proposed K by the researcher is 12, and the K resulting from the model is 13. Considering the 8.5% difference in the K results, 13 have been selected). The 13 selected variables are called non-fragile, and the rest of the variables, which have a lower probability of entering later than the previous probability, are called fragile. According to table 6, the 13 variables in the presence of all variables have a higher posterior probability than their previous probability. The effect of these variables on financial wealth can be investigated, and in other words, these variables are significant due to the increased probability of these 13 variables in the model. The variables' posterior coefficients and posterior standard deviations are presented in the third and fourth columns, respectively. In the last column, the statistic of the t-ratio for each variable is provided. Variables with the highest t-ratio are of greater importance to financial solvency. The priority of impactful variables on financial solvency is displayed in the last column. In the Bayesian averaging method, the results are obtained based on the value of the meta parameter k (k was assumed to be 12 in the above calculations), and this question is raised: if the results and meta parameter value change, how much is the change? In other words, does the model's expected size selection affect the results? Consequently, the results were compared by choosing different $\overline{K}$s and redoing the sampling process and related calculations. The model space and, therefore, the variables and data remain consistent in these three scenarios, and the only difference is the model's expected size. However, it is quite apparent that changing the model's expected size alters the samples. Consequently, the outcomes differ, i.e., variables may be fragile (or non-fragile) in all three values of $\overline{K}$. The fragility of some variables may change with the value of $\overline{K}$, and a variable considered fragile under one $\overline{K}$ becomes non-fragile with an increased expected size of the model.

Table 6: Prioritization of variables affecting financial prosperity in the optimal model

Priority	**Regressions with** $2 \geq \lvert t-stat \rvert$	**The first sample contains 4 million regressions**		**Variable**
		Posterior probability	**Posterior coefficient**	
2	0.861	0.723	0.185	Economic growth
1	0.932	0.926	0.036	Inflation uncertainty
3	0.858	0.764	0.007	Exchange rate
13	0.464	0.514	0.046	Sanction
9	0.584	0.518	0.036	Liquidity ratio
10	0.575	0.664	0.227	Return on working capital
11	0.506	0.548	0.046	Return on capital ratio
8	0.618	0.727	0.000	Debt ratio
7	0.646	0.632	0.754	Total debt to equity ratio
4	0.788	0.741	0.152	The ratio of long-term debt to equity
12	0.491	0.503	0.018	Surplus contribution (through reinsurance) to Surplus
5	0.772	0.923	0.185	Return on investment
6	0.701	0.896	0.180	Adjusted liabilities to current assets

Considering that the non-fragile variables in the case of $\overline{K}$=12 and $\overline{K}$=10 with $\overline{K}$=8 have a higher posterior probability, the researcher can use a different K, considering the small difference (below 10%). The researcher investigated the more complete state (with more K) due to the increased comprehensiveness of the research. The final variables were determined by applying the double research conditions (Figure 3).

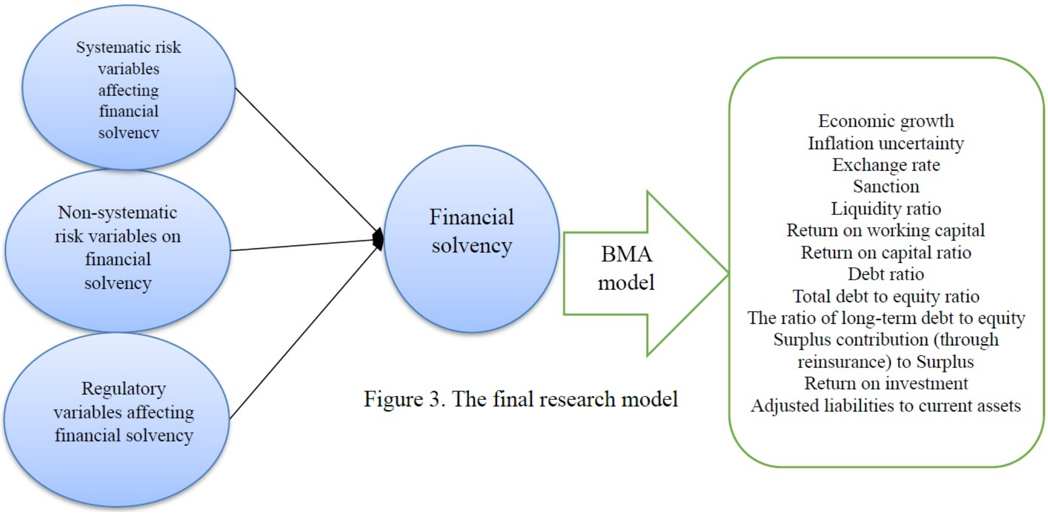


Figure 3: The final research model

5 Conclusion and policy proposals

Financial distress and bankruptcy can cause resource wastage and missed investment opportunities in insurance companies. Researchers can alert insurance companies to the occurrence of bankruptcy by examining the factors affecting financial solvency to adopt appropriate policies based on these warnings. On the other hand, participants in financial and money markets need awareness and knowledge of the financial status of existing companies. The importance of using appropriate models and techniques is because they should be determined according to the conditions of the insurance market of each country. Therefore, the present study aimed to model and identify the non-fragile variables affecting insurance companies. Thus, information on 40 factors affecting financial solvency was entered into BMA, TVP-DMA, TVP-DMS, and BVAR models. Based on error rates, the BMA model had the highest accuracy. A total of 13 non-fragile variables were identified after the estimation of the model, including economic growth, inflation uncertainty, exchange rate, sanctions, liquidity ratio, return on equity ratio, debt ratio, total debt to equity ratio, long-term debt to equity ratio, surplus aid (via reinsurance) to surplus, return on investment, and adjusted liabilities to current assets.

In this study, an experimental relationship analysis demonstrated that relying on a single conceptual model in the financial solvency modelling process leads to inaccurate predictions, and ultimately, management decisions regarding that model will face the risk of failure in forecasting. According to the results, many factors affecting financial solvency are a warning that a systemic perspective is essential in managing an insurance company. Merely considering a specific model or a set of particular variables cannot provide a comprehensive view of determining the industry's optimal model of financial solvency. The findings of this research are in line with the results of [1, 3, 25, 40, 50, 56, 64, 73, 74]. Consequently, designing a comprehensive approach that considers Iran's environmental conditions will make the research model more efficient compared to other models. Based on the research findings, the following policy recommendations can be presented:

Compared to traditional models, the Bayesian model is consistent regarding high predictive power. Investors, financial analysts, capital banks, investment companies, and brokers of the Tehran Stock Exchange are suggested to use this model to evaluate the financial situation of Iranian insurance companies and make decisions related to their investments. In addition, using this model by the stock exchange organisation to accept companies in the stock market helps to evaluate the examined insurance more accurately. Financial solvency is multidimensional; therefore, employing a systemic model that examines all aspects of this phenomenon is recommended for designing early warning models. Stakeholders often utilise company rankings and assessments of their operational continuity; hence, it is suggested that all investors and stakeholders in this industry use the proposed models of the current research separately for industries alongside other reviews and analyses. Given the significance of sanctions, entering global insurance markets should be on the agenda of insurance company managers. Considering the importance of economic growth and inflation uncertainty on financial solvency, implementing supply-side policies should be prioritised since these policies, if implemented, would shift the aggregate supply curve rightward and downward, facilitating economic growth and reducing inflation.

Regulation No. 69, entitled "Regulation on the Calculation and Supervision of the Financial Solvency of Insurance Institutions," approved by the High Council of Insurance by paragraph 5 of Article 17, considering Articles 40 and 59 of the Law on the Establishment of Central Insurance of Iran and Insurance Operations, and in the execution of Article 114 of the Fifth Five-Year Development Plan of the Islamic Republic of Iran (2011-2015), was passed on 26/11/1390 in 15 articles and two notes. In this regulation, financial solvency is defined as "the financial ability of the insurance institution to cover its accepted risks." It can be reviewed by examining and comparing new methods and the efficiency of each one. Given the recent bankruptcy of an insurance company and its detrimental effects on the country's insurance industry, the continuous oversight of regulatory bodies using modern and forward-looking methods utilised worldwide has become significantly important.

Insurance companies should develop their management structure to establish risk management systems and internal controls to establish corporate governance and respond to stakeholders to provide high-quality insurance services. A suitable governance structure is a prerequisite for an efficient risk management system and financial wealth. Insurance companies can reduce operational risks and design organizational strategies more optimally by evaluating factors related to the supervision and control of internal organizational processes and employing skilled personnel at various levels. Insurance organizations can lay the groundwork for controlling the credit risk factor within the company through optimal assessment and control of risk-inducing factors, thereby controlling bankruptcy and ensuring greater profitability for their shareholders. Correct division of work, appropriate selection of people, paying attention to the psychological aspects of work and employees, creating fields of intellectual creativity and strengthening the morale of employees, and paying attention to discipline in work and the work environment are necessary to increase efficiency and increase coordination between managers at different levels. Meanwhile, the role of managers and supervisors in benefiting from the "art of management" stands out next to the science of management. Managers and supervisors using the control and leadership contingency policy can take the main step in increasing the efficiency of people from the above factors according to different conditions, which ultimately improves the productivity of organizations and effectively helps in achieving the goals.

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